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An approach of vessel collision risk assessment based on the D–S evidence theory

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ABSTRACT

Computing time and decision correctness are the measurable indicators in vessel collision risk (CR) assessment. However, the existing CR assessment approaches, based on fuzzy theory or neural network, have lower accuracy and longer computing times. To overcome these drawbacks and obtain a compromised evaluation, an approach of vessel CR assessment based on the Dempster–Shafer (D–S) evidence theory is proposed in this paper. Considering that CR is associated with the membership functions corresponding to navigation parameters such as the distance to the closest point of approach (DCPA), the time to closest point of approach (TCPA) and the relative distance, we use the multiradar network to achieve them. Afterwards, applying the D–S evidence theory, we successfully assess CR with joint basic probability assignment (JBPA). Finally, the simulation results confirm the validity of the proposed approach.

1. Introduction

Owing to brisk economic growth, marine traffic has been developing rapidly nowadays. Regarding improving shipping efficiency, we are facing challenging issues on account of continuous growth in vessel number and vessel size. When the vessels run into busy waterways and/or linking ports, there is a high potential for collision. Although the collision is often closely related to the navigator's behavior, the ever-changing navigation environment still has irreversible impact on the ship's navigation; see, for example, Zhao and Wang (1999), Zheng and Wu (2000) and the references therein. The study by Shih et al. (2012) reveals that more than 60% of vessel collisions are caused by hostile environments. As powerful impetus, these works in the field of ocean engineering prompted the research on vessel collision avoidance. It is well known that collision avoidance started from assessing collision risk (CR). The concept of vessel domain was first proposed by Fujii and Tanaka (1971) among the several definitions of CR. Currently, the main scope of work done by Wang (2012) relates to the CR assessment method under poor navigation conditions. Since the assessment depends on subjective factors of the navigator and objective factors of the environment, the relevant research has been an oft-discussed maritime issue at home and abroad.

In recent years, several oceanographers have studied these fields with a great deal of success and many papers with respect to vessel CR assessment have been published in some important international journals. Research work conducted by Xu et al. (2009), Su et al. (2012), Ahna et al. (2012) and Bukhari et al. (2013) demonstrate vessel CR assessment in various ways. A fuzzy method for determining the radius of guarding ring for collision avoidance was studied by Shi et al. (2008). Furthermore, Pundlik and Luo (2012) introduced tracked feature points to obtain a set of feature points that most likely represent the potential obstacle based on the threshold step. The assessment by Perera et al. (2012) consists of a fuzzy-theory-based parallel decision-making module whose decisions are formulated into sequential actions by a Bayesian-network-based module. Considering the required ship turning, the fuzzy monitoring system put forward by Su et al. (2012) suggests the optimal rudder steering procedure for the give-way ship to avoid collision. Meanwhile, in the work carried out by Park et al. (2011), the multilayer perception neural network is applied by utilizing the Monte Carlo method. However, the essences of all the aforementioned works are based on the fuzzy theory or the neural network. Owing to some drawbacks of the two algorithms, vessel CR assessment is limited in practical engineering. First, the fuzzy-theory-based CR assessment is considered as a synthesis algorithm using the Boolean operator. In the discourse domain, the vessel with the greatest membership of CR is regarded as the most dangerous target. However, as early as in 2000, Zheng and Wu (2000) pointed out the assessment uncertainty when the target ships have ambiguous membership of CR. In contrast, it is difficult for the neural network to obtain a large number of sample set or to converge in the training stage with multiparameter. Furthermore, the training time significantly

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increases as the complexity of network structure increases, which leads to the reduction of learning ability (Xu et al., 2003). Compared with the algorithms based on the fuzzy theory or on the neural network, the Dempster–Shafer (D–S) evidence theory – which has a strong theory foundation – can well eliminate the information uncertainty and make full use of the evidence of multisource information to improve assessment accuracy (Surya et al., 2000). Tu and Xu (2001) showed that the hypothesis set that depends on the accumulative evidence on the D–S evidence theory can achieve fast convergence without a priori probability and conditional probability. However, a few works on the D–S evidence theory have been reported to complete vessel CR assessment at the present stage.

In this paper, we propose an approach to vessel CR assessment based on the D–S evidence theory, which can resolve the associated issues of collision avoidance. First we apply the information fusion theory to calculate the membership functions corresponding to the distance to the closest point of approach (DCPA), the time to the closest point of approach (TCPA) and the relative distance r among every ship from the vessel traffic system (VTS) center using a multiradar network. Later, the extracted membership functions are transformed into the joint basic probability assignment (JBPA) and CR is calculated according to the D–S evidence theory. To confirm the performance of the proposed algorithm, we used the required data from a radar processing system to carry out simulation experiment and displayed the degree of CR among all the ships. The remainder of this article has been arranged as follows: Section 2 discusses the calculation of DCPA, TCPA and r. In Section 3, we use the D–S evidence theory to achieve the degree of CR. Section 4 discusses the simulation results about the CR assessment among many vessels. In the last section, we sum up the paper by providing scope for future work.

2. Preliminaries

In 2002, the International Maritime Organization (IMO) adopted new maritime security measures that include amendments to the 1974 Convention of Safety of Life at Sea (SOLAS) as well as a new mandatory International Ships and Port Facilities Security (ISPS) code. The studies by Johansen et al. (2004) and Liu (2006) show that the values of DCPA, TCPA and r from every encounter ship are important navigation parameters, which should be accurately calculated in the VTS center. In this section, we present the representations corresponding to the DCPA, TCPA and r based on the information fusion theory.

2.1. Representations of DCPA, TCPA and r

We suppose that the velocity and the course of the own ship are v_0 and c_0, respectively, with geographic position point (x_0, y_0). Similarly, v_T and c_T denote the velocity and the course, respectively, by indicating (x_T, y_T) as the geographic position point for the target ship (Ahna et al., 2012; Tu and Xu, 2001). To calculate the navigation parameters, we utilized the coordinate system.

Fig. 1 demonstrates their relationships and shows that the relative distance between two ships is

$$r=\sqrt{(x_T-x_0)^2+(y_T-y_0)^2} \tag{1}$$

Applying the cosine theorem, we obtain the relative velocity in the vector triangle $\Delta v_0 v_T v_R$.

$$v_R=\sqrt{v_0^2+v_T^2-2v_0 v_T\ \cos(c_T-c_0-\pi)} \tag{2}$$

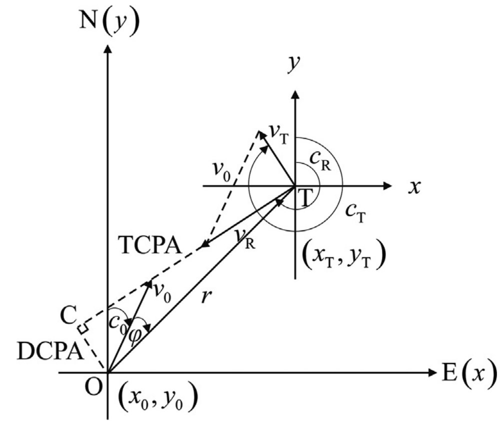

Fig. 1. Important parameters in the coordinate system.

Then the relative course can be calculated as follows:

$$c_R=\begin{cases} c_0-\arccos\left(\frac{v_R^2+v_0^2-v_T^2}{2v_R v_0}\right), & c_0<c_T \\ c_0+\arccos\left(\frac{v_R^2+v_0^2-v_T^2}{2v_R v_0}\right), & c_0\geq c_T \end{cases} \tag{3}$$

Subsequent to the above parameters, we obtain the DCPA in the collision triangle ΔOCT by applying the sine theorem. As one right side OC, the DCPA is considered as one right side OC, which can be written as

$$\mathrm{DCPA}=r\ \sin(c_R-c_0-\varphi-\pi) \tag{4}$$

where φ is the bearing between the own ship and the target ship.

Similarly, we can see that the TCPA is the quotation of the other right side CT and v_R in ΔOCT, i.e.,

$$\mathrm{TCPA}=\frac{r}{v_R}\ \cos(c_R-c_0-\varphi-\pi) \tag{5}$$

In Eqs. (4) and (5), it can be seen that DCPA and TCPA are not separated in the analysis of vessel collision; they reflect the collision possibility and the collision degree. Ren et al. (2011) explained that DCPA and TCPA are dependent on the length and speed of the ship, respectively. Since their values are determined by r, the corresponding observation errors should be reduced as much as possible.

2.2. Achieving fusion from multiradar network

As a special sensor, the radar can detect and indicate all the relevant targets on the water surface regardless of any onboard equipment. Because it has the advantage that it can detect small vessels and floating objects, the radar has been widely applied in maritime communications. In the process of multitarget tracking (MTT), the single radar can hardly estimate the number of targets and their states from a sequence of noisy and cluttered measurement sets. In contrast, the multiradar network can improve the tracking accuracy by reducing the randomness of the stochastic oscillator sequence at every moment in overlapping areas (Ling et al., 2000). Therefore, we utilized a multiradar to achieve the navigation parameters by rule and line. In the interest of simplicity, we use the subscript j to denote the DCPA, TCPA and r (j=1, 2, 3).

Suppose k radars can simultaneously observe the same target ship (k=1, 2,…, K), then the jth fusion result at time t can be calculated by using the following equation:

$$F_j(t)=\sum_{k=1}^{K} w_k c_{jk}(t) \tag{6}$$

where $c_{jk}(t)$ is the jth input of the kth radar with mean of a_k and variance of σ_k^2, w_k is the normalized weighted coefficient corresponding to $c_{jk}(t)$ which satisfies $\sum_{k=1}^{K} w_k = 1$. According to the multivariate statistical law, we know that $F_j(t)$ also follows the normal distribution (Tu and Xu, 2001), i.e., $F_j(t) \sim N(\sum_{k=1}^{K} w_k a_k, \sum_{k=1}^{K} w_k^2 \sigma_k^2)$. Consequently, we use the Lagrange multiplier algorithm to calculate w_k (Wu et al. 2010). Assuming the Lagrange multiplier is λ, we have the Lagrange function

$$L(w_k, \lambda) = \sum_{k=1}^{K} w_k^2 \sigma_k^2 + \lambda \left(\sum_{k=1}^{K} w_k - 1 \right) \tag{7}$$

Setting the above equation derivations to zero, we get

$$\begin{cases} \frac{\partial L}{\partial w_k} = 2 w_k \sigma_k^2 + \lambda = 0 \\ \frac{\partial L}{\partial \lambda} = \sum_{k=1}^{K} w_k - 1 = 0 \end{cases} \tag{8}$$

Solving Eq. (8), w_k can be obtained as follows:

$$w_k = \frac{1}{\sigma_k^2 \sum_{k=1}^{K} (1/\sigma_k^2)} \tag{9}$$

Substituting the above equation into Eq. (6), $F_j(t)$ can be finally achieved.

$$F_j(t) = \sum_{k=1}^{K} \frac{c_{jk}(t)}{\sigma_k^2 \sum_{k=1}^{K} (1/\sigma_k^2)} \tag{10}$$

Remark 1. We briefly prove the reliability of the related work as mentioned above. For a single radar, the standard deviation σ_k mainly determines the accuracy of $F_j(t)$ (Zhao and Wang, 1999). Suppose $\sigma_{k\,\min}$ and $\sigma_{k\,\max}$ correspond to the high-accuracy radar and the low-accuracy radar in the multiradar network, respectively. Similarly, we deduce the accuracy of $F_j(t)$ is as follows:

$$\begin{aligned} \sigma_j &= \sqrt{\sum_{i=1}^{n} w_k^2 \sigma_k^2} \\ &= \sqrt{\sum_{k=1}^{K} \frac{\sigma_k^2}{(\sigma_k^2 \sum_{k=1}^{K} (1/\sigma_k^2))^2}} \\ &= \frac{1}{\sqrt{\sum_{k=1}^{K} (1/\sigma_k^2)}} \\ &= \frac{1}{\sqrt{(1/\sigma_{k\,\min}^2) + (1/\sigma_{k\,\max}^2) + \sum_{k=1}^{K-2} (1/\sigma_k^2)}} \\ &< \frac{1}{\sqrt{1/\sigma_{k\,\min}^2}} \\ &= \sigma_{k\,\min} \end{aligned} \tag{11}$$

In Eq. (11), we can see that the predictor accuracy of a multiradar network is less than that of any single radar and the low-accuracy radar has little influence on $F_j(t)$. Therefore, our preliminaries have characteristics of more precise values.

3. Methodology

It is well known that the D–S evidence theory is a flexible mathematical tool for handling uncertain and incomplete information and tackles the prior probability issue by keeping track of an explicit probabilistic measure of a possible lack of information. Considering that the influence of DCPA, TCPA and r is different, the D–S evidence theory is applied to combine BPAs, regarded as evidences, to derive a compelling assessment in this section.

3.1. Determination of membership functions

The membership function can describe information by expressing the evidence that the amplitude is, to a certain degree, either large or small. First we propose a set of standard membership functions according to the regulations (VTS & SAFE NAVIGATION) of SOLAS.

Let the safe distance of approach be d_L, which can be defined as

$$d_L = \begin{cases} 1.1 - \frac{0.2\varphi}{180^\circ}, & 0^\circ \le \varphi \le 112.5^\circ \\ 1.0 - \frac{0.4\varphi}{180^\circ}, & 112.5^\circ \le \varphi \le 180^\circ \\ 1.0 - \frac{0.4(360^\circ - \varphi)}{180^\circ}, & 180^\circ \le \varphi \le 247.5^\circ \\ 1.1 - \frac{0.2(360^\circ - \varphi)}{180^\circ}, & 247.5^\circ \le \varphi \le 360^\circ \end{cases} \tag{12}$$

Consequently, we find that the safe passing distance is twice the safe distance of approach, i.e., $d_U = 2d_L$. Suppose that the membership function is falling ridge distribution type for actual calculation. Then, for the ith ship, we have the membership function corresponding to the DCPA.

$$\mu_1(s_i) = \begin{cases} 1, & \mathrm{DCPA} \le d_L \\ \frac{1}{2} - \frac{1}{2} \sin\left[\frac{\pi}{d_U - d_L} \left(\mathrm{DCPA} - \frac{d_U + d_L}{2} \right) \right], & d_L < \mathrm{DCPA} \le d_U \\ 0, & \mathrm{DCPA} > d_U \end{cases} \tag{13}$$

We define the collision time and the avoidance time as follows:

$$t_L = \frac{\sqrt{r^2 - \mathrm{DCPA}^2}}{v_R}, \quad t_U = \frac{\sqrt{12^2 - \mathrm{DCPA}^2}}{v_R} \tag{14}$$

In our work, the TCPA follows the uniform distribution in [t_L, t_U]. Then we know that the corresponding membership function obeys the falling parabolic distribution.

$$\mu_2(s_i) = \begin{cases} 1, & \mathrm{TCPA} \le t_L \\ \left(\frac{t_U - \mathrm{TCPA}}{t_U - t_L} \right)^2, & t_L < \mathrm{TCPA} \le t_U \\ 0, & \mathrm{TCPA} > t_U \end{cases} \tag{15}$$

Suppose the distance of the last action is r_L determined by vessel length; similar to Eq. (13), we can conclude that the membership function corresponding to r is

$$\mu_3(s_i) = \begin{cases} 1, & r \le r_L \\ \left(\frac{r_U - r}{r_U - r_L} \right)^2, & r_L < r \le r_U \\ 0, & r > r_U \end{cases} \tag{16}$$

where r_U is the distance of action, i.e.,

$$r_U = 1.7 \cos(\varphi - 19^\circ) + \sqrt{4.4 + 2.89 \cos^2(\varphi - 19^\circ)} \tag{17}$$

In Eqs. (13), (15) and (16), the membership functions increase as the DCPA, TCPA and r decrease. Liu and Liu (2000) and Chin and Debnath (2009) showed that $\mu_1(s_i)$ has an important influence on vessel CR assessment. If it is zero, there is no collision between the two ships. Otherwise, $\mu_2(s_i)$ and $\mu_3(s_i)$ should be considered together further.

3.2. Determination of JBPA

Unfortunately, the different membership functions may lead to different assessments. If the membership functions are very ambiguous, a wrong assessment will occur inevitably. To solve this problem, we introduce BPA according to the D–S evidence theory, which can make the membership function an independent variable to support a given hypothesis.

Assuming there are i ships (i=1, 2,…, S) and every ship has j membership functions, then we can have the maximum membership function as follows:

$$\alpha_j = \max \{\mu_j(s_i)\} \tag{18}$$

Suppose that the normalized weighted factor is ε_j, the maximum relative membership function is

$$\beta_j = \frac{\varepsilon_j \alpha_j}{\sum_{i=1}^{S} \mu_j(s_i)} \tag{19}$$

Further, the reliability coefficient in this work can be defined as (Jia, 2007; Han et al., 2010)

$$\gamma_j = \frac{\alpha_j \beta_j}{\sum_{j=1}^{3} \alpha_j \beta_j} \tag{20}$$

In Eq. (20), $\alpha_j\beta_j$ represents both crosswise comparison between the most dangerous ship and others in the same membership function and longitudinal comparison among the different membership functions (Mou et al., 2010).Wang and Li (2011) and Gargiulo et al. (2012) have provided some modified combination rules to compute BPA. In this work, we use the following equation to express the normalized BPA:

$$m_j(s_i) = \frac{\mu_j(s_i)}{\sum_{i=1}^{S} \mu_j(s_i) + 3(1-\gamma_j)(1-\alpha_j\beta_j)} \tag{21}$$

Since the sum of all BPAs for each hypothesis is equal to 1, we have the uncertain BPA:

$$m_j(\Theta) = 1 - \sum_{i=1}^{S} m_j(s_i) \tag{22}$$

According to the D–S evidence theory, JBPA based on two membership functions can be written as

$$\begin{aligned} m_{1\cap 2}(s_i) &= m_1(s_i) \oplus m_2(s_i) \\ &= \frac{\sum_{p_1 \cap p_2 \neq \Phi} m_1(s_{p_1}) m_2(s_{p_2})}{1 - \sum_{p_1 \cap p_2 = \Phi} m_1(s_{p_1}) m_2(s_{p_2})} \\ &= \frac{m_1(s_{p_1}) m_2(s_{p_2}) + m_1(s_{p_1}) m_2(\Theta) + m_1(\Theta) m_2(s_{p_2})}{1 - \sum_{p_1=1}^{S} m_1(s_{p_1}) \sum_{\substack{p_2=1 \\ p_2 \neq p_1}}^{S} m_2(s_{p_2})} \end{aligned} \tag{23}$$

Similar to Eq. (22), the uncertain JBPA can be written as

$$m_{1\cap 2}(\Theta) = 1 - \sum_{i=1}^{S} m_{1\cap 2}(s_i) \tag{24}$$

Finally we deduct JBPA of three membership functions as follows:

$$\begin{aligned} m_{1\cap 2\cap 3}(s_i) &= m_1(s_i) \oplus m_2(s_i) \oplus m_3(s_i) \\ &= m_{1\cap 2}(s_i) \oplus m_3(s_i) \\ &= \frac{\sum_{i \cap p_3 \neq \Phi} m_{1\cap 2}(s_i) m_3(s_{p_3})}{1 - \sum_{i \cap p_3 = \Phi} m_{1\cap 2}(s_i) m_3(s_{p_3})} \\ &= \frac{m_{1\cap 2}(s_i) m_3(s_{p_3}) + m_{1\cap 2}(s_i) m_3(\Theta) + m_{1\cap 2}(\Theta) m_3(s_{p_3})}{1 - \sum_{i=1}^{S} m_{1\cap 2}(s_i) \sum_{\substack{p_3=1 \\ p_3 \neq i}}^{S} m_3(s_{p_3})} \end{aligned} \tag{25}$$

Remark 2. In Eq. (25), it can be seen that $m_{1\cap 2\cap 3}(s_i)$ represents the degree of CR. The larger the JBPA, the higher the CR. The belief of evidence gives us the certainty level of results, where a maximum of belief will be considered in decision-making. Therefore, the priority of CR should be arranged in descending order when the own ship encounters multiple target ships, where the target ship with the maximum JBPA can be considered as the most dangerous vessel.

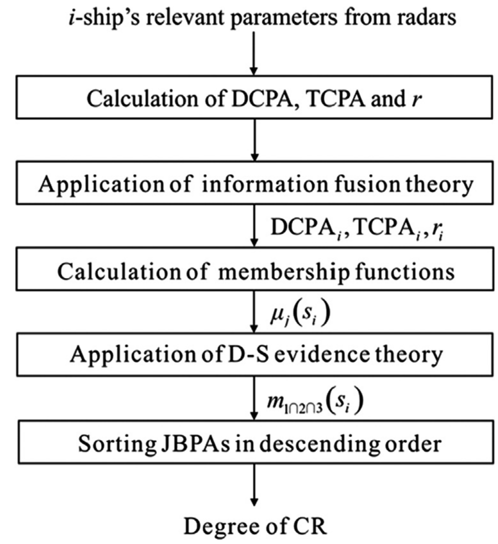

Fig. 2. Flowchart of vessel CR assessment.

Fig. 2 shows the basic architecture of the proposed assessment approach.

4. Simulation results and discussions

Our experimental environment was as follows: Intel CPU @2.9 GHz, RAM 4 GB, Window XP. Many experiments are developed with our radar processing system (see Fig. 3) programmed using Visual C++, which can obtain inputs from multiple radars. Here, we introduce three representative scenarios to validate the performance of the proposed approach in the VTS center.

4.1. Scenario 1

In scenario 1, we apply a simple structure, 2-radar network, to process the information from five target ships in a busy waterway. Fig. 4 illustrates the DCPA, TCPA and r of target ships. It can be seen that their fluctuations (dotted lines) are larger using the single S-type or single X-type radar. On the contrary, the fusion results (solid lines) are obviously smooth when the normalized weighted coefficient ratio between S-type radar and X-type radar is set to 1:5.9735.

In addition, Table 1 cites the accuracy of navigation parameters. It is obvious that the standard deviation σ_j is significantly reduced using a multiradar. In other words, the reliability is effectively improved compared with any single radar.

4.2. Scenario 2

In scenario 2, we evaluate the membership function of each ship using the parameters in Table 2. Fig. 5 shows the values of these membership functions. From this figure, the maximum value of membership function corresponding to the DCPA, TCPA and r can be achieved from ships 3, 4 and 4 in turn. However, we can see there is a big difference among the three membership functions for a certain ship. For instance, ship 3 has the largest $\mu_1(s_3)$,

Fig. 3. Screenshot of the radar processing system.

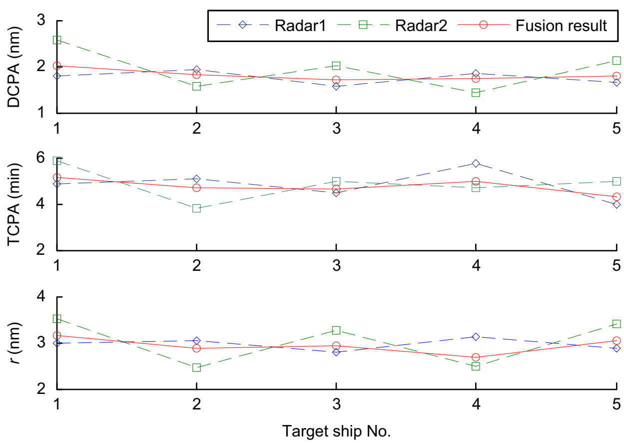

Fig. 4. Diagram of TCPA, DCPA and r.

Table 1
Standard deviation σ_j.

	X-type radar	S-type radar	2-radar network
σ_1	0.1445	0.5401	0.1396
σ_2	0.1800	0.5117	0.1698
σ_3	0.1467	0.2133	0.1208

whereas $\mu_2(s_3)$ and $\mu_3(s_3)$ are relatively smaller. Therefore, it is difficult for us to make the final decision.

Subsequently, we calculate the BPAs of five target ships. Fig. 6 shows the detailed numerical results. Setting $m_{1\cap 2\cap 3}(s_i)$ against any single m_j, we find a clear improvement. By sorting $m_{1\cap 2\cap 3}(s_i)$ in descending order, the CR sequence is achieved (ships 4, 3, 5, 2, 1). At the same time, we can conclude that ship 4 is the most dangerous, ship 1 is the safest and the other three target ships are medium.

4.3. Scenario 3

In scenario 3, we used another group of membership functions provided in Table 3 to validate the calculation performance. The results obtained by using the proposed approach and a comparison of the results with two popular methods provided in Zheng and Wu (2000) are given in Table 4. From the results, the computing time of the BP-neural-network-based algorithm is found to be longer and the correctness of the fuzzy-theory-based approach is found to be lower. A comparison shows that the results based on the D–S evidence theory have high accuracy with compromised time.

Table 2
Parameters from 2-radar network.

	Ship 1	Ship 2	Ship 3	Ship 4	Ship 5
Speed (nm)	16.37	12.81	20.07	15.93	20.97
Course (deg)	119.75	160.03	243.15	101.48	135.29
Bearing (deg)	9.48	30.65	3.57	0.91	10.63
DCPA (nm)	2.0155	1.8256	1.7158	1.7289	1.7858
TCPA (min)	5.1518	4.6738	4.6201	4.9936	4.2832
r (nm)	3.14	2.87	2.93	2.69	3.03

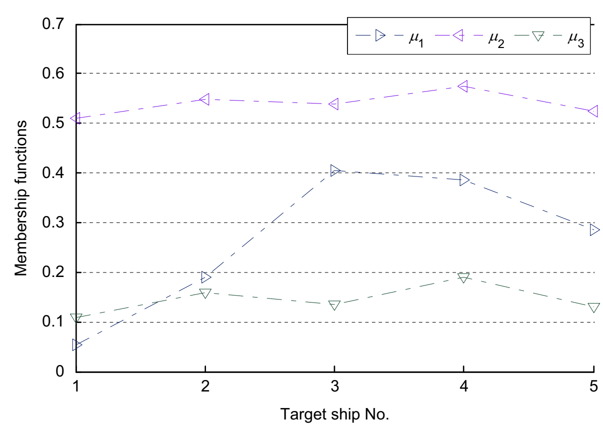

Fig. 5. Diagram of membership functions.

5. Conclusion

In this paper, an approach for vessel CR assessment is studied using the D–S evidence theory. We used a multiradar network to calculate navigation parameters such as the DCPA, TCPA and r, by applying the information fusion theory. Then according to the

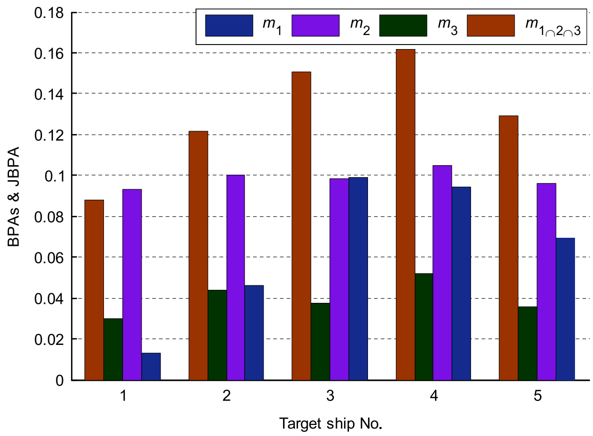

Fig. 6. Diagram of BPAs and JBPA.

Table 3
Membership functions of target ships (No.6–10).

	Ship 6	Ship 7	Ship 8	Ship 9	Ship 10
μ_1	0.912	0.694	0.554	0.000	0.593
μ_2	0.093	0.857	0.625	0.127	0.000
μ_3	0.198	0.131	0.117	0.095	0.125

Table 4
Comparative performance.

	Correctness (%)	Computing time (s)
Fuzzy-theory-based approach	90	0.932
BP-neural-network-based approach	100	1.415
Proposed approach	100	1.137

D–S evidence theory, we introduced the membership function and JBPA to assess CR. During the simulation, we concluded that the proposed approach can effectively overcome the drawbacks of the existing schemes and can smoothly evaluate the degree of CR. It is easy to see that our approach not only has some theoretical significance but also has more far-reaching effects. However, there is a limitation of this approach in that the computing time is compromised. Therefore, methods of reducing computational complexity as much as possible should be considered in future research.

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